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The effect of environmental and operational variabilities on damage detection in wind turbine blades

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Abstract

It is a well-known fact that changes in the environmental and operational conditions may seriously influence the performance of structural health monitoring (SHM) methods. The present paper demonstrates how certain environmental and operational variations affect the damage detection in the blade of an operating wind turbine. The considered vibration-based SHM setup was measuring blade accelerations over a period of 3.5 months, while simultaneously recording the environmental and operational conditions. In the period, a damage of three different sizes was introduced by gradually cutting open the trailing edge of the blade. The damage index used in the study is composed of Mahalanobis-squared distances based on the covariance matrix of the accelerations. It is demonstrated how temperature and wind speed along with rotational speed and pitch can mask the damaged-induced changes, hence leading to false-negative classifications. It is found that the highest correlation exists between the damage index and variabilities in the temperature and rotational speed. Limiting the operational variabilities by using correlated measurements and filtering out the environmental variabilities by principal component analysis provides a clear detection of the three introduced damages.

1. Introduction

The first objective of vibration-based structural health monitoring (SHM) is to detect if damage is present in the structural system based on a measured dynamic response (1). Many of the developed methods operate on the premise that structural damage will alter the dynamic response compared to that of a measured reference state. The structure is considered damaged if the two states differ by more than a pre-determined threshold. However, challenges arise when changes in the measured response are due to environmental or operational variabilities, as these can mask the ones caused by structural damage, hereby leading to false-negative classifications (3), (4).

This paper examines the influence and possible mitigation of certain environmental and operational variables in the context of detecting damage in an operating wind turbine blade. The damage detection is conducted using a damage index composed of Mahalanobis-squared distances based on the covariance matrix of accelerations (2). This damage index has previously proven successful in the same SHM setup (2), where blade accelerations were measured over a period of 3.5 months on a fully operational Vestas V27 wind turbine. The detection study in (2) employed the transient response induced by an electromechanical actuator mounted on the blade, while the current study applies solely the rotational motion of the blade. In the measurement period, the environmental and operational conditions were recorded, while a damage of three different sizes was introduced by gradually cutting open the trailing edge of the blade. The recorded environmental and operational conditions are compared individually to the damage index with the objective of outlining the influence of each variability on the damage detection. The variabilities that influence the damage detection are presented together with the damage index to make any tendencies apparent.

The paper is built as follows; the experimental setup is described in section 2, followed by the theory behind the damage detection scheme in section 3. The influence of the environmental and operational variabilities are presented in section 4 together with some damage detection results, and, finally, a discussion and some concluding remarks are given in section 5 and 6.

2. Experimental setup

The Vestas V27 wind turbine treated in this study, seen depicted in figure 1a, has been a subject of multiple SHM studies and is, as such, described thoroughly in previous work (2), (5), (6). Consequently, only a summary of the experimental campaign is given here.

The campaign was conducted throughout the winter of 2014/2015 over a period of 3.5 months, where a damage of three different sizes was introduced in the trailing edge of the blade. The initial damage stretched 15 cm and was extended first to 30 cm and then to 45 cm. The largest damage of 45 cm is illustrated in figure 1b.

a) **b)**

Figure 1. Vestas V27 wind turbine; a) ground view; b) the 45 cm damage.

The vibration response of the blade was measured normal to its surface using 11 accelerometers located at the positions depicted in figure 2, which also shows the location and extent of the three damages. Azimuth angle, pitch angle and rotational speed were also measured and recorded.

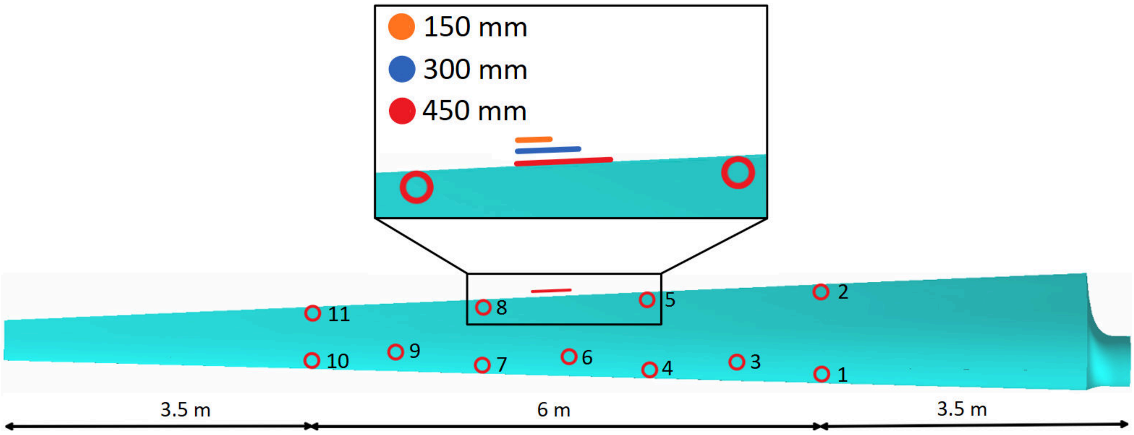


Figure 2. The locations of the 11 accelerometers marked with red circles and number, while the position and extent of the damage are marked with the red, blue and orange lines.

The measurement system sampled with a frequency of 16,384 Hz over a period of 30 seconds every 5 minutes. The blade was equipped with an electromechanical actuator, which is not used in this study, as only the rotational motion of the blade is utilized in the damage detection analyses. The impact from the actuator has fully decayed after 13.5 s and figure 3 shows a typical vibration signal for the last 16.5 s from accelerometer 1.

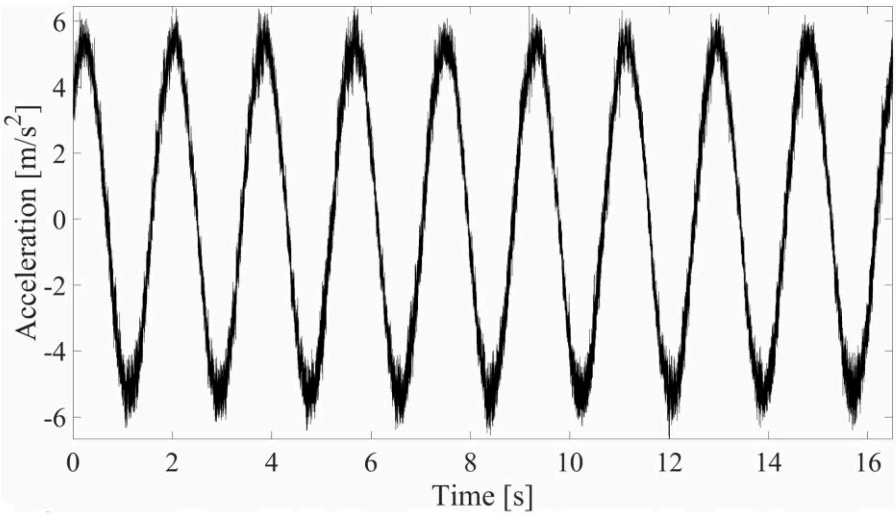


Figure 3. Typical acceleration signal for 16.5 seconds from accelerometer 1.

Simultaneously with the vibration measurements, the weather data was recorded from a 45 m high meteorological mast located 60 m from the wind turbine. These recordings contained wind speed, temperature, precipitation and wind direction averaged over one minute. The operating condition, produced power and yaw angle were also extracted from the control system in the wind turbine.

3. Damage detection methodology

The detection scheme used in this study is based on a semi-supervised approach, where the accelerations from a healthy reference state are known. These accelerations are employed to create a baseline, which any new experiments are tested against on the premise that significant deviation indicates damage. Following (2), a change in measured vibration signals is reflected in the covariance matrix taken from those signals, which thus provides a measure of the similarities between each sensor. The covariance matrix of accelerations for N sensors is a symmetric $N \times N$ matrix and the amount of unique elements in the matrix is equal to $C = N(N+1)/2$. The unique elements are stored in a so-called feature vector $y_j \in \mathbb{R}^{C\times 1}$ for each experiment $j \in [1, m]$, with m designating the total amount of experiments. The Mahalanobis-squared distance is computed for the j^{th} experiment by

$$D^2(y_j) = (y_j - \mu)^T \Sigma^{-1} (y_j - \mu), \tag{1}$$

where $\mu \in \mathbb{R}^{C\times 1}$ and $\sum \in \mathbb{R}^{C\times C}$, respectively, designate the mean and covariance of the training set, $x \in \mathbb{R}^{C\times n}$, obtained from n healthy state feature vectors. The Mahalanobis-squared distance functions as the damage index, as it provides a quantified difference between the training set and a new experiment.

To classify when the structure is damaged, a threshold based on extreme value statistics is applied by fitting distribution functions to a training set of healthy data and setting the threshold based on a commonly applied confidence level of $\alpha = 0.99$ (2).

The Mahalanobis-squared distances will contain environmental and operational variabilities, which must be accounted for in the post-processing. Principal component analysis (PCA) is a well-known linear method for filtering out the environmental effects by projecting the feature vector into subspaces of minor and major components (5). If the major components have been identified to contain the variabilities, these are removed, hence only the minor components are kept when computing the Mahalanobis-squared distances. A common choice of removal is 99.9% of the variance belonging to the major components (4).

4. Damage detection results

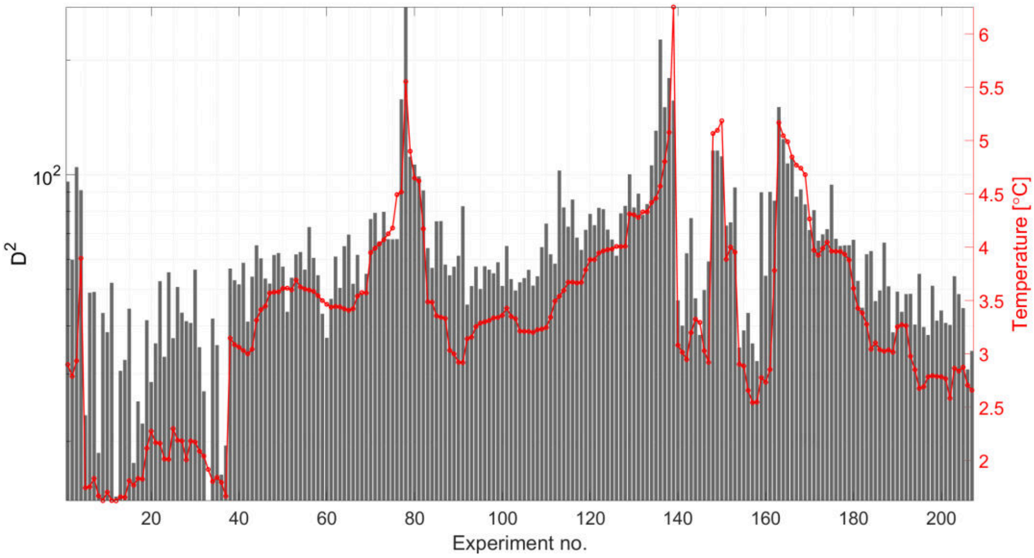
The measured environmental and operational data are used to expose the variabilities affecting the damage detection. The parameters that influence the damage detection are presented in section 4.1, and the damage detection results, where the parameters are accounted for using PCA, are presented in section 4.2.

4.1 Environmental and operational effects

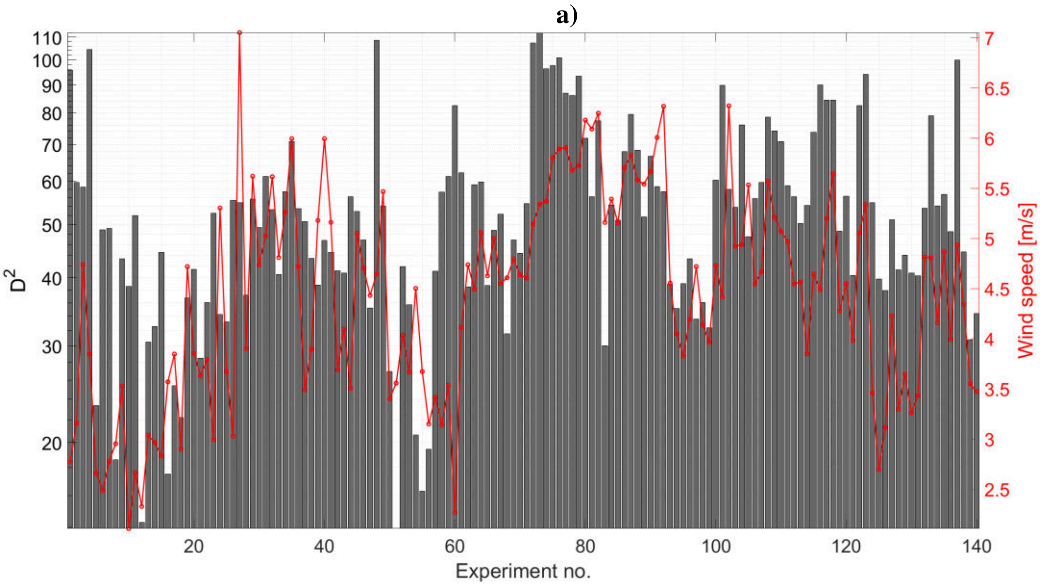
To characterize the influence of the environmental and operational variabilities on the damage detection, only one parameter is allowed to vary at a time, while the remaining parameters are held constant. The parameters tested for having an impact on the damage detection index are: temperature, wind speed, pitch angle and rotational speed. Temperature and wind speed are well-known to cause issues in SHM schemes (3), (4), while the mentioned operational parameters intuitively change the conditions between the measurements. The pitch angle will alter the measurement direction of the accelerometers with respect to a ground-fixed coordinate system, while the rotational speed will alter the static deflection of the blade due to changed wind pressure. It needs to be noted that both considered operational parameters are automatically set by the wind turbine control system, depending on the instant wind speed.

The correlation between the damage index and the environmental and operational variabilities are presented using only healthy state measurements to omit any non-linear effects the damage can introduce. Hence, healthy state samples are used for both training and testing. In each of the cases, 60 samples with the lowest varying environmental or operational values are used for training, leaving the remaining samples for testing.

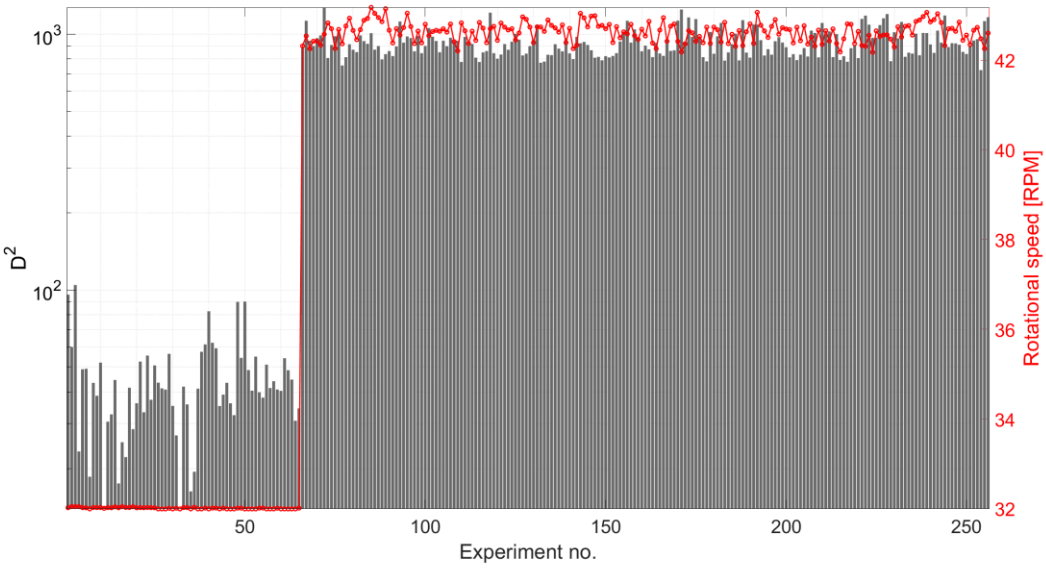
Figure 4a, 4b and 4c illustrate the tendencies between the damage index and the temperature, wind speed and rotational speed. All three parameters show a clear correlation with the damage index, with the highest correlation appearing for the temperature and rotational speed. The pitch angle does not show a clear tendency when illustrated, but analyses show that it has a significant impact on the detection results if not accounted for.



a)



b)



c)

Figure 4. Tendencies between the variabilities (red dots) and the damage index (grey bars); a) Temperature at 32 RPM; b) Wind speed at 32 RPM; c) Rotational speed.

4.2 Detection results

This section presents two damage detection analyses based on the two operational regimes (32 RPM and 43 RPM) of the wind turbine. Only samples with a rotor RPM in the range of [31.95, 32.05] and [42.10, 43.10], both within a pitch angle range of [-0.5, 0.5], are used in the analyses. The environmental variabilities are allowed to vary, as these are accounted for by PCA. For the 32 RPM case, these specifications yield the following number of measurements: 856 (healthy), 59 (15 cm damage), 95 (30 cm damage) and 106 (45 cm damage). The training set in equation 1 is computed based on 80% of the healthy state data, which was found in analyses to provide the fewest amount of false-positives. This corresponds to the finding in (4), where at least 60-80% of healthy state data in the training was found to be optimal. The remaining healthy state data is used for testing the threshold.

Three probability density functions are fitted to the training set to find a distribution function representing the data, such that a threshold can be computed based on a chosen confidence level. This approach is preferable when outliers might exist in the training set, as thresholds based on, for example, maximum values herein are sensitive to disturbances. Figure 5 depicts three distribution functions, Weibull, Gumbel and Frechet, fitted to a normalized histogram of the training set computed from 32 RPM measurements.

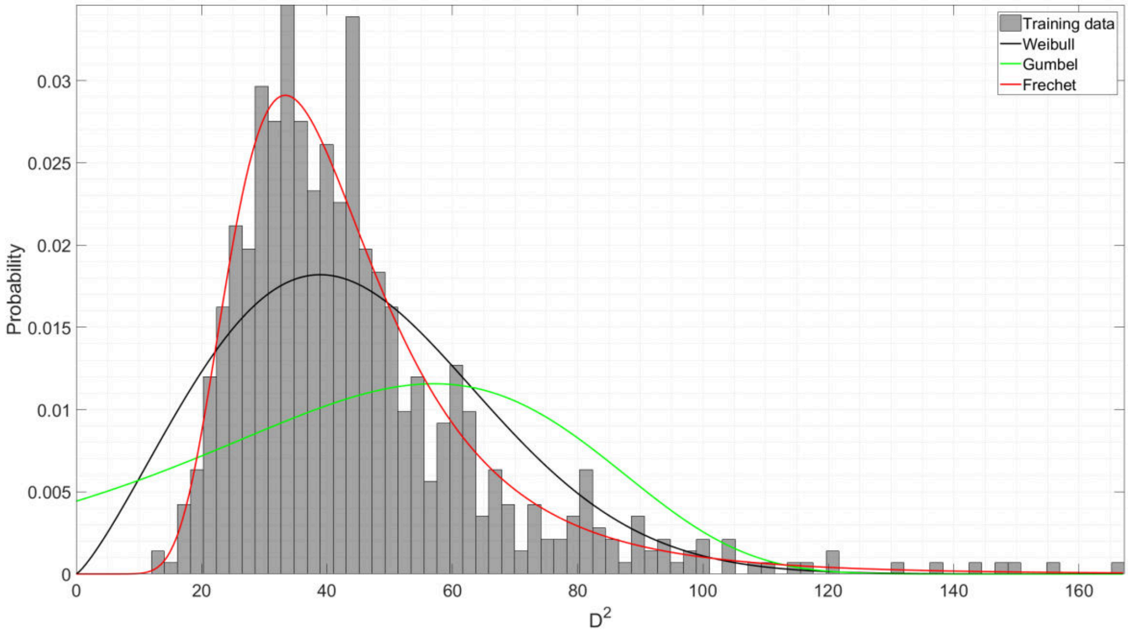


Figure 5. A histogram of training data from the 32 RPM regime and the tested probability distribution functions, Weibull, Gumbel and Frechet.

It is evident from figure 5 that a Frechet distribution provides the lowest error for the 32 RPM measurements and the same was observed for the 43 RPM case. Hence, the threshold is computed for the 32 RPM and 43 RPM regimes based on the Frechet distribution with the earlier mentioned confidence level of $\alpha = 0.99$.

The thresholds are plotted in figure 6 and 7 with a blue horizontal line together with the respective Mahalanobis-squared distances computed based on the 32 RPM and 43 RPM regimes. Some expected false-positives exist in the healthy state since the threshold is computed based on a confidence level of $\alpha = 0.99$.

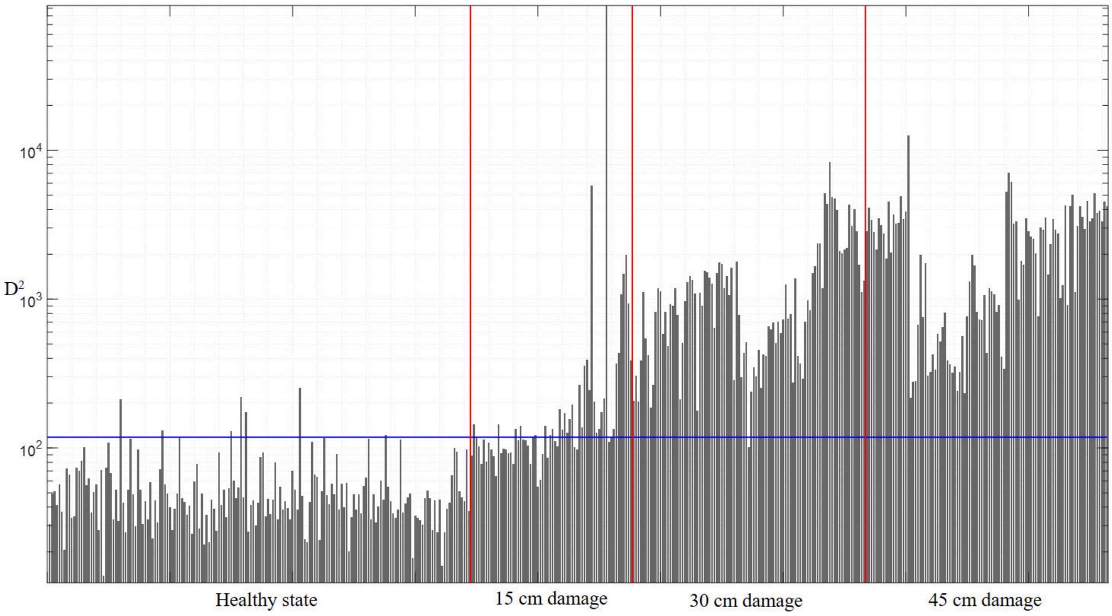


Figure 6. Mahalanobis-squared distances marked with grey bars computed from 32 RPM data series. The threshold is marked with a blue horizontal line, and the different states are marked with red vertical lines.

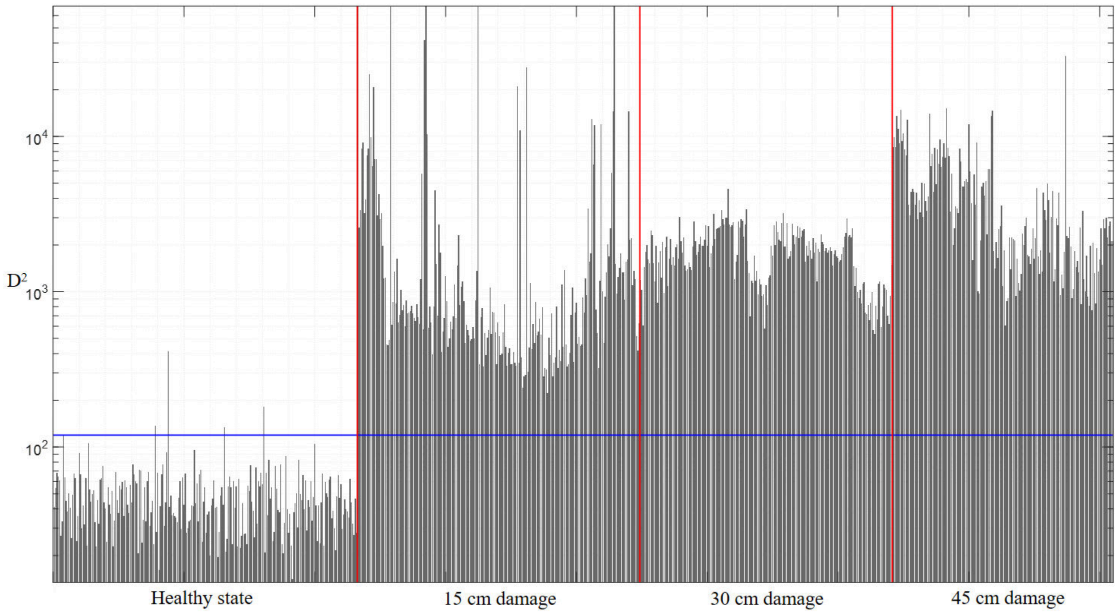


Figure 7. Mahalanobis-squared distances marked with grey bars computed from 43 RPM data series. The threshold is marked with a blue horizontal line, and the different states are marked with red vertical lines.

The damage in the second state, a 15 cm crack, is detected 100% of the time when using the 43 RPM data series, while 45% false-negatives exist for the 32 RPM series. It is noted that when PCA is not included, 61% false-negatives exist for the 32 RPM regime. The 15 cm damage is, thus, only consistently detectable for the 32 RPM regime if a low confidence level is set on the number of allowable outliers to distinguish between healthy and damaged states. However, a low confidence interval increases the threat of a false-positive detection, thus setting of the confidence level is a trade-off between the allowable risk and the associated cost.

The 30 cm and 45 cm cracks are clearly detected using both operational regimes, as only one false-negative exist when using the 32 RPM regime to detect the 30 cm crack. When comparing figures 6 and 7, it is seen that the 43 RPM regime provides higher differences between the Mahalanobis-squared distances in the healthy and damaged states compared to the 32 RPM regime. Thus, detection of damages in wind turbine blades based on higher rotational speeds seems preferable.

5. Discussion

A comparable damage detection analysis using the same covariance-based feature was performed in (2), where the earlier mentioned actuator was used for detection in the same setup during turbine operation at 32 RPM. In the study, all three crack stages were successfully detected without any false-negatives using a similar approach of limiting the range on the rotational speed and pitch, and applying PCA for dimensionality reduction. When comparing the detection resolution of the 32 RPM case in the two studies, the actuator-based approach seems superior (as expected), but it naturally requires that the structure is accessible for mounting the actuator.

6. Conclusions

The present paper demonstrates the correlation between a Mahalanobis distance-based damage index and environmental and operational parameters, namely, temperature, wind speed, rotational speed and pitch angle. The highest correlation is found to exist for the temperature and rotational speed.

It is demonstrated that a 15 cm long trailing edge damage can be detected (albeit with a substantial amount of false-negatives for the 32 RPM regime) using only the rotational motion of the blade by limiting the operational parameters and applying PCA analysis to reduce the environmental effects. Additionally, it is demonstrated that when the damage is increased to 30 cm and 45 cm the detection becomes unambiguous. Finally, it appears that higher rotational speeds provide a higher damage detection rate, as the difference between healthy and damaged state increases.

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